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# An Automatic Procedure for Multidimensional Temperature Signal Analysis of a SCADA System with Application to Belt Conveyor Components

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**Abstract**

In this paper, a problem of interpretation and analysis of multidimensional temperature data acquired using an online monitoring system is presented. It is highlighted, that apart from the data acquisition system there is a strong need to use automatic decision-making rules. A classical *if then else* approach i.e. the comparison of a current value of temperature with a priori assumed threshold is not possible due to the cyclic nature of machine operation and the influence of external factors as ventilation system or bulk material stream conveyed on the belt. Moreover, these thresholds are unknown and might themselves depend on the mentioned factors. It should be also noted, that in industrial data acquisition systems, there is a high probability of external disturbances, meaning that the signals should be validated and pre-processed first. Indeed, we noticed outliers related to the data acquisition system operation. The cyclic variability of temperatures has no diagnostic meaning and makes the interpretation of data and decision making difficult. In this paper, we propose an automatic data processing framework how to extract diagnostic information and present it in a user-friendly manner. The analysed example data comes from a belt conveyor used in underground mining.


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*Keywords:* SCADA; time-varying systems; belt conveyor; temperature measurements.

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## 1. Introduction

The dynamic growth of data acquisition and transmission systems provided a great opportunity to measure many physical variables in order to monitor technological processes, as well as the condition of machines during their operation online. This is especially important in underground mines, where the natural hazard level is rather high and environmental conditions are often difficult for miners. Using SCADA systems to acquire important parameters, one might extract information about process efficiency as well as machine condition. However, monitoring systems are often too much focused on acquisition and visualization of raw data. In practical application in industry, especially in mining, acquired data are difficult to interpret due to external disturbances (noise, missing values, etc.) and the complexity of monitored processes/systems. In this paper, a procedure for processing and analysis of multidimensional temperature data is presented. A data acquisition system has been introduced to the network of belt conveyors (see Fig. 1) with many monitored components (electric motors, gearboxes, pulleys etc. – see Fig. 2). Due to the large number of monitored objects, there is a need to use automatic decision making and reporting tools. The number of channels for each conveyor depends on its design. Depending on the location of the belt conveyor, its “cold” temperature (no operation) might be different and is seriously related to local conditions and the given mining area’s ventilation efficiency. Conveyors do not operate continuously due to the used mining technology (room and pillar with blasting). It means that every day, there is a downtime or work without external load (so called idle gear) related to, for example, blasting procedure (or even technological or maintenance issues). Moreover, Sunday is free day for miners and conveyors do not operate at all, unless repair procedures are applied. Such events cause a significant change of temperature that can be easily visible on temperature plots. Unfortunately, these fluctuations in long term perspective make diagnosis very difficult. As it was expected, there is a need to validate the signal and remove some outliers from the raw data.

The purpose of this paper is to propose a procedure for the pre-processing and transformation of data to acquisition simple information about the variation of temperature that is related to changing conditions in the machine and it is not affected by operational factors. Ideally, the expected result should be a monotonic function of time with clear breakpoints related to any change of condition of the machine.

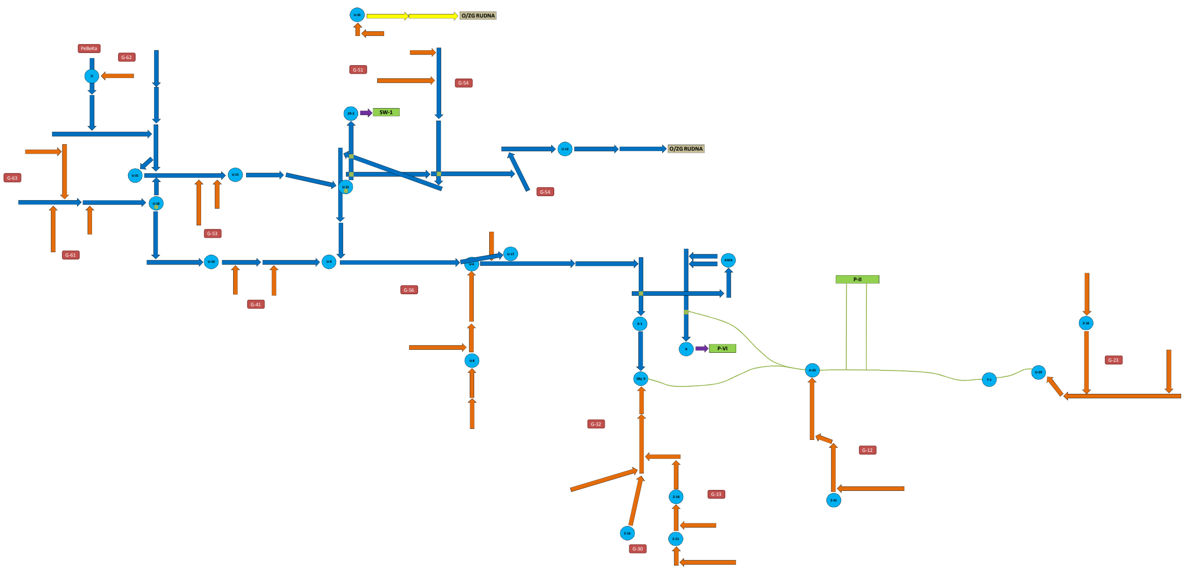


Fig. 1. Structure of belt conveyor network in O/ZG Polkowice-Sieroszowice underground mine.

## 2. The data acquisition system. Input data description

The data acquisition system used in the mine is a commercial, multichannel low frequency data logger working in continuously. To avoid a massive amount of data, especially for really low frequency processes, the sampling procedure for a physical variable is not performed constantly. The system stores the value of a variable only if it differs from the previous value more than a priori assumed threshold.


Fig. 2. Localization of temperature sensor mounted on conveyor gearbox.

Such a solution significantly reduces the amount of data, but leads to much trouble from the signal processing perspective. First, each channel might have a different number of samples for the same period of time. Samples are non-uniformly distributed over time, and they are not synchronized with other channels, so even a simple comparison between channels is difficult. Due to the variable sampling period, such a signal cannot be considered as a time series and has to be pre-processed first. Figure 3 presents examples of 4 channels of temperature data from gearboxes. The analyzed period covers one month. One might notice 4 sections related to 4 weeks of operation. On Sundays, when machines are not in operation, temperature drops significantly to ambient temperature in underground corridors. During the week, there is cyclic behavior of temperature that needs to be investigated. In the signal, several samples seem to be incorrect (temperature is negative, and therefore far exceeds the possible temperature analyzed in the underground mine, which varies from +28 ºC to 38 ºC). From Fig. 3 (presentation of raw data) it is extremely difficult to conclude about any change of condition. However, simple visualization of all channels on one plot allows noticing that one of channels (plotted in red in second section – from 22.02.15 to 01.03.15) seriously changed and its temperatures are higher. Section 3 of the chart (01-08.03.15) presents a similar change also for another channel (plotted in blue) but is more difficult to notice .

One might conclude, that there is a serious need to "clean" the data, segment the signal (remove observations acquired on Sunday – no operation during that time) and somehow transform the data to obtain a new representation with clear diagnostic meaning (monotonic function that depends on change of condition, not on operating or ambient temperature).

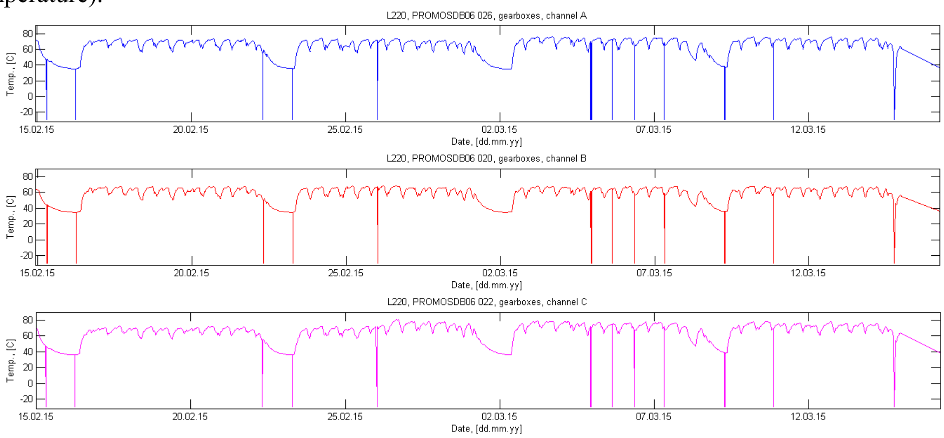


Fig. 3. Example of acquired data – temperatures.

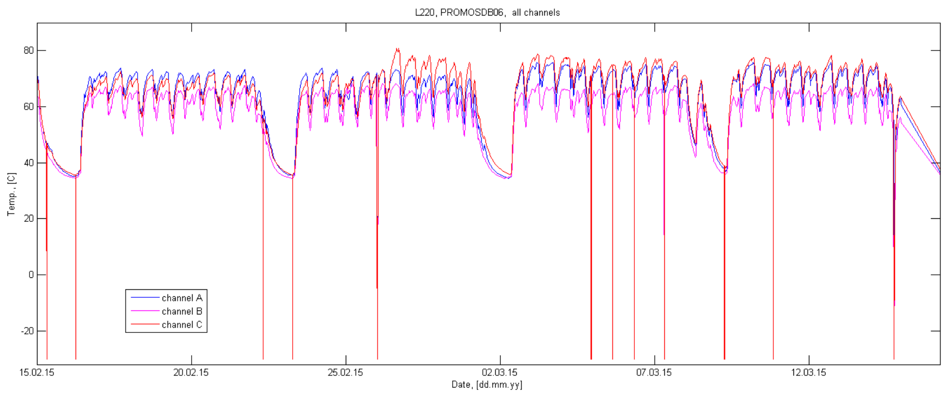


Fig. 4. Comparison of all channels: gearboxes.

## 2. An automatic procedure for md signal processing

As it was mentioned, SCADA systems are often used to monitor some physical variables with simple comparison with thresholds to provide warning or alarm messages for the maintenance staff. Unfortunately, in harsh and time varying conditions there is a need to put some efforts to prepare data for further processing. In next sub-sections, we will provide a brief state of the art how it works in other – not necessarily mining - applications and some crucial steps will be pointed out.

### *2.1. Brief state of the art*

Among other industrial applications, a market of green energy is rapidly growing nowadays and number of condition monitoring systems installed on wind turbines is impressive. Consequently, number of papers considering data analysis for wind turbine monitoring systems is large [1-5]. Indeed. it is worthy to analyse this field for several reasons. There is a serious analogy between wind turbines and mining machines due to variability of load/speed conditions, influence of environmental factors, number of object that need maintenance in single wind farm etc. Analysis of wind turbines data presented in [15] confirm that validation, pre-processing, transformation of raw data is required in industrial applications and fully converge to challenges related to mining machines.

Searching for direct mining industry application of SCADA systems and data processing acquired thanks to installed systems might provide also interesting papers with exactly the same problems as mentioned above. In fact it might be related to different mining machines and structures (LHD machines, longwall systems, conveyors etc) [6-14]. From this paper's perspective especially interesting applications refer to conveyor as whole system, or its components (belts, drive, idlers, bearings, gearboxes). It might be surprising, that considered problem might be very similar for different physical variables, so even when temperature signals are investigated, it might be worthy to look for solutions developed for vibration signals.

An attempt of holistic view on industrial data processing for consition monitoring and performance evaluation was presented in [14] where monitoring system developed for self-propelled mining machines in underground mine was presented. As mentioned earlier, validation of the data was highlighted both for mining and wind energy applications [14,15]. Signal segmentation for industrial data has been discussed in [15], where the method initially developed for other applications [17] has been extended and applied to rotational speed processing in LHD machines [16]. In this paper, segmentation is required to extract data related to single week without Sunday break. Nowadays, monitoring systems allow acquiring many channels simultaneously. These data might be also transformed and parametrized so consequently multidimensional data set should be analyzed. There are some interesting papers focused on this subject published by Cempel and recently by Zimroz &Bartkowiak [18,19]. Indispensable consequence of multidimensional data acquisition and processing is redundancy. In other words, acquired data or extracted parameters are somehow correlated to each other and share similar information. To reduce computational cost and complexity of the diagnostic system, especially on the decision making stage, one can benefit from techniques focused on dimentionality reduction. There are several approaches of variable selection or data transformation. Probably the most popular technique is Principal Component Analysis. Deep study of practical diagnostics applications of data dimesionality reduction might be found in [18-20]

Probably the most critical issue in CM systems is determining the warning/alarm threshold. [21-24]. There is a need to establish it for every machine type and, moreover, even for different context (ambient temperature, load of the machine, other factors as ventilation in underground mine). In many cases, there are no good condition/ bad condition references available. One of possible solutions is to identify good condition and monitor variation from this state (so-called anomaly detection). Alternative approach might be tracking of behavior (not only the exact value) of the diagnostic feature. As mentioned, multidimensional data analysis might be profitable here – by simultaneous analysis of many channels we can neglect influence of ambient temperature and operational context ( it might be considered as exactly the same in one mining corridor and for the same conveyor).

### *2.2. Preprocessing: Outlier removing*

In statistics, an outlier is an observation point that is distant from other observations. An outlier may occurr due to variability in the measurement, it may indicate experimental error or it may be a result of specific pre-processing (e.g. logarithm of data with some near-zero values). In the data temperature that we analyze here we also observe the outliers (see Fig. 3 and 4), thus in the first step of the analysis we have to remove them from the time series. Outliers removing in this case is a simple procedure. It is based on finding negative values of temperature and replacing them – for the simplicity – by the previous sample. Fig. 5 presents 4 weeks data after outliers removing.

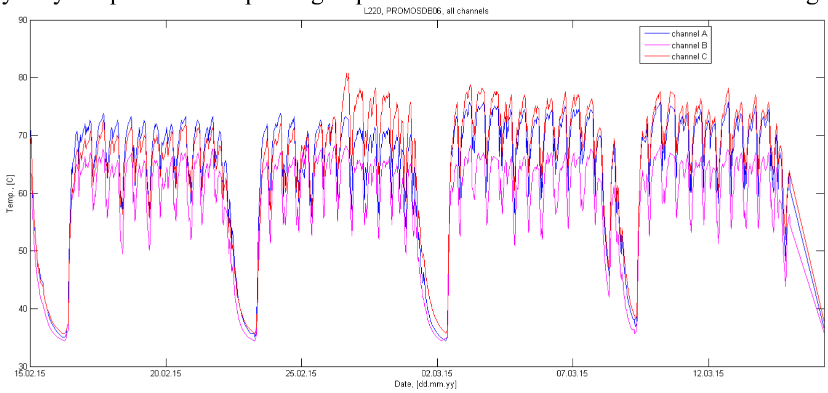


Fig. 5. Signals after outliers removing.

### *2.3. Preprocessing: Resampling – data are not uniformly sampled*

The analyzed data are not uniformly sampled, thus in the next step we should resample the vector of observations in order to analyze the time series. Let us mention, a time series is a sequence of data points, typically consisting of successive measurements made over a certain time interval. In order to resample the data we use the linear interpolation, which is a method of curve fitting using linear polynomial. Linear interpolation is often used to approximate a value of some function (or process) using two known values of that function at neighboring points. There are also other methods of interpolation applicable in this case, although the linear interpolation seems to be the most appropriate one. The interpolated values cannot excess the neighboring real values – in such a case the data acquisition system would have indicated such significant temperature change. Linear interpolation is also consistent with another physical property of the considered data – relatively slow variations of temperature in considered machines.

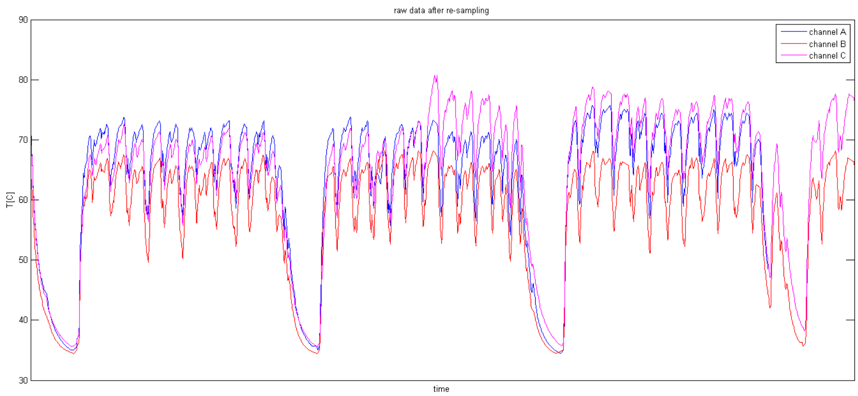


Fig. 6. Signals after resampling.

### 2.4. Segmentation – data reveal cyclic behavior

Raw signals presented in previous figures reveal seasonal behavior. Between significant fluctuations for some period of time (one week), there are also short cycles (several cycles per week) of rising and dropping temperature. In our opinion, there is a need to divide whole observation into pieces with homogenous behavior. From Fig. 5 one might easily notice 4 cycles of data. We divided whole signal into 4 pieces and analyze the first 3 ones, presented in Fig. 6 and Fig. 7.

### 2.5. Model and Decomposition of the signal

Based on our observation we propose a model of raw signal S(t) that could be expressed as:

$$S(t)=P(t)+F(t)+N(t), \tag{1}$$

where the function P(t) represents the deterministic trend generally described by the polynomial of given order, F(t) is a deterministic periodic function that represents seasonal fluctuations in the data while N(t) is a random process (called noise). The representation given in equation (1) corresponds to so-called Wold's decomposition, where the model of the signal also consists of three components described above. From diagnostic perspective, the most important information contain the trend component P(t). It should be related to change of machine condition.

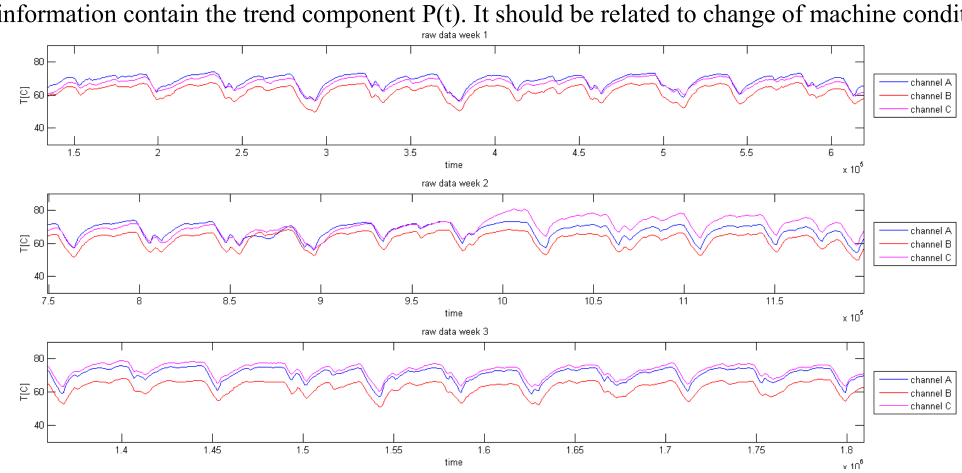


Fig. 7. Signals after resampling, each plot represent all channels readings through one week.

## 2.6. Detrending

As it will be mentioned earlier, it was found that each segment is constituted from two main components with different properties. The first one, commonly used in diagnostics is a trend-like signal. It stands for slow variation of the machine temperature that depends on time of operation, condition of the machine, temperature in the given mining corridor underground, etc. Second process is very different. It is related to relatively high frequency fluctuation of temperature and it corresponds to time varying machine operation. To identify and understand both components, it is proposed to decompose the signal into deterministic trend and residual signal related to the mentioned fluctuations (we ignore noise component here due its very small energy). So, in the next step for each specified sub-signal we fit a polynomial which represents the deterministic trend. In order to fit the polynomial corresponding to each sub-signal we use the least squares method. Denoting the sub-signal as $Y_1, Y_2, \dots, Y_m$, the coefficients $a_1, a_2, \dots, a_p$. of the polynomial of order $p$ are calculated by solving the following equation:

$$(a_0, a_1, \dots, a_p) = \operatorname{argmin} \sum_{i=1}^{m} r_i^2, \tag{2}$$

where $r_i$ is a residuum corresponding to the observation i, i.e. value defined as follows:

$$r_i = Y_i - \sum_{j=0}^{p} a_j i^j, \qquad i = 1,2,\dots,m \tag{3}$$

and

$$f(i) = \sum_{j=0}^{p} a_j i^j, \qquad i = 1,2,\dots,m \tag{4}$$

is the fitted polynomial of given order p. Let us mention, that the minimum in equation (2) is taken with respect to all coefficients $(a_1, a_2, \dots, a_p.)$ that belong to the real number set. In the analysis performed in the next section we fit the polynomials of order 4 to each sub-signal from the real temperature signals.

Fig.8 presents raw signals and the trend component. As it can be seen, trend signals follow low frequency variation of the signal.

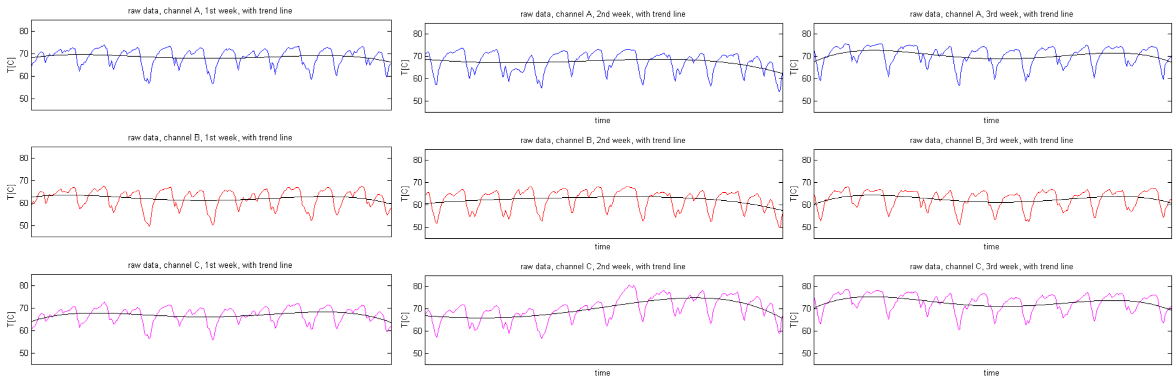


Fig. 8. Raw signals with trend component (black lines).

## 2.7. Decision making on the basis of trend signals

We assume that diagnostic information is carried by low frequency trend signals. In this section, we will try to understand behavior of trend signals and analyse if the amplitude of trend signal could be used as indicator of technical condition.

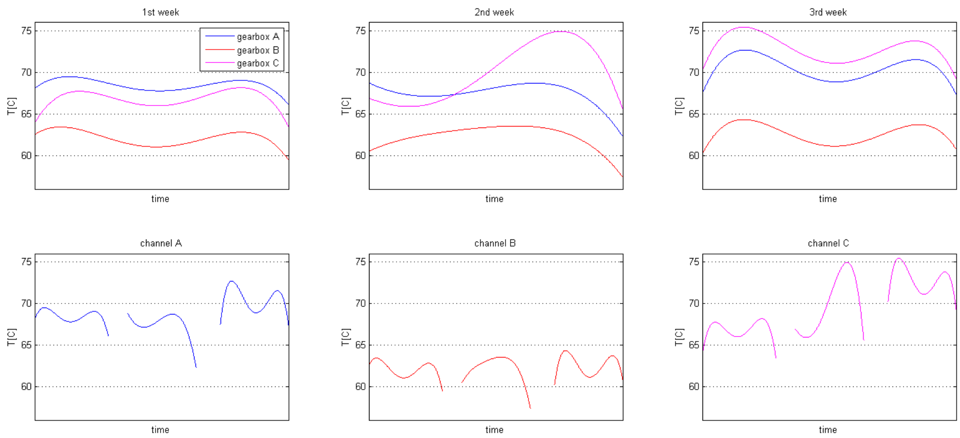


Fig. 9. Trend signals analysis: top panels: all channels analysed within a single week; bottom raw: each channel analysed separately for whole investigated period.

Fig. 9 presents behavior of trend signals for each channel and for each week. From week 1 one might easily notice that temperature for Channel B (machine B) is the smallest, and Channel A is the largest. All signals fluctuate a bit in the same way. Analysis of data for Week 2 brings novel view. Channel B is still on the same level, similarly to channel A, however, channel C becomes nearly 10 ºC higher. It points out change of condition of machine C. Analysis of week 3 provides even more findings. Machine C is still much warmer than 2 weeks ago and, additionally, temperature of machine A became higher, as well. Bottom panels show the same data but each plots presents only one signal for 3 weeks. It is even better visible that machine A changed its condition in week 3, machine B is still working properly and machine C changed condition during mid of week 2. It should be said, that change of temperature might be still biased by environmental or operational factors. However, by analysis of 3 channels on the same drive station, we can investigate if change of condition is related to change of condition, or to other reasons (all signals should behave in the same way).

### *2.8. Identification of seasonality (weekly, daily seasons)*

As mentioned, a seasonal behavior might be clearly visible in the raw data. After resampling of raw data to get constant sampling frequency, one might use spectral analysis to identify duration of cycles (frequencies). However, it is better to remove trend before spectral analysis to get zero mean signals. In Fig. 10 signals after trend removal are presented.

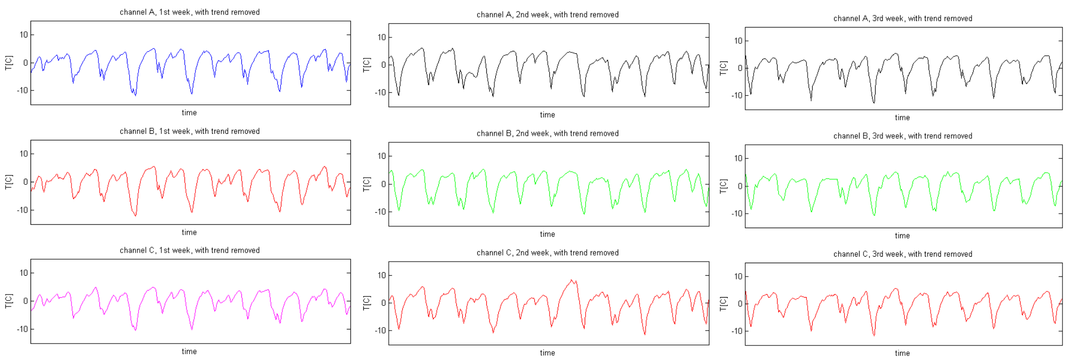


Fig.10. Raw data after trend removal.

In Fig. 11 power spectral density (PSD) of these signals are presented. Structure of the spectrum is nearly the same. There are three main components related to three cycles: 24h, 12h and 6h. These cycles correspond to cyclic mining technology used in the considered mine.

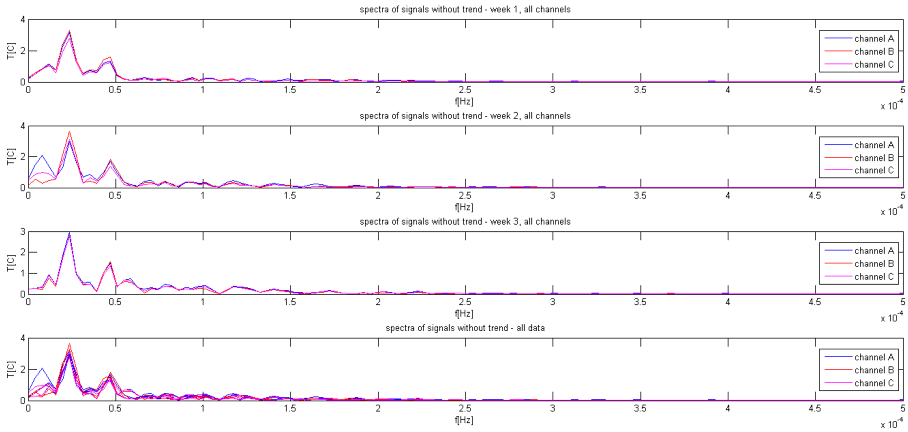


Fig.11. Spectra of raw signals after trend removal.

Table 1. Frequencies and cycles identification.

| No | Freq | Period [s] | Period [h] | comment |
|---|---|---|---|---|
| 1 | 0.00001172 | 85324.23 | 23.70118 | Daily cycle |
| 2 | 0.00004688 | 21331.06 | 5.925294 | Shift cycle |
| 3 | 0.00002344 | 42662.12 | 11.85059 | 2* Shift cycle |

## 3. Conclusion

In the paper problem of SCADA temperature data analysis is presented. It is highlighted that apart from data acquisition system there is a strong need to use automatic decision making algorithms. There is proposal of procedure of processing and analysis of multidimensional temperature data. It has been developed as dedicated tool for belt conveyor drive unit diagnostics, particularly for gearboxes and pulleys used in drive units. The proposed framework allows to extract data diagnostic information which provides an opportunity of taking right actions in order to prevent possible damage of belt conveyor components.

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## References

1. Yang, W., Little, C., Tavner, P.J., Court, R., 2014. Data-driven technique for interpreting wind turbine condition monitoring signals, IET Renewable Power Generation 8/2, , pp 151-159
2. Guo, P., Infield, D., Yang, X., 2012. Wind turbine generator condition-monitoring using temperature trend analysis.IEEE Transactions on Sustainable Energy, 3 (1), art. no. 5970135, pp. 124-133. doi: 10.1109/TSTE.2011.2163430
3. Astolfi, D., Castellani, F. , Terzi, L., 2014. Fault prevention and diagnosis through SCADA temperature data analysis of an onshore wind farm, Diagnostyka 15/2, , pp 71-78
4. Yang, W., Court, R., Jiang, J., 2013. Wind turbine condition monitoring by the approach of SCADA data analysis. Renewable Energy, 53, pp. 365-376.
5. Wilkinson, M., Darnell, B., Van Delft, T., Harman, K., 2014. Comparison of methods for wind turbine condition monitoring with SCADA data, IET Renewable Power Generation, 8 (4), pp. 390-397.

6. Eliasson, J., Kyusakov, R., Martinsson, P.-E., Eriksson, T., Oeien, C., 2013. An internet of things approach for intelligent monitoring of conveyor belt rollers, 10th International Conference on Condition Monitoring and Machinery Failure Prevention Technologies 2013, CM 2013 and MFPT 2013 2, pp. 1096-1104.
7. Sadhu, P.K., Chattopadhyaya, S., Chatterjee, T.K., Mittra, D.K. 2008. Online monitoring and actuation for curing of rubber conveyor belts, Journal of the Institution of Engineers (India): Mechanical Engineering Division 89, pp 31-35.
8. Zhang, X., Fan, T.-N., 2012. The research of distribute temperature monitoring system early warning fire in coal belt conveyor , Advanced Materials Research 548 , Pages 890-892.
9. Wei, Y., Wu, W., Liu, T., Sun, Y., 2013. Study of coal mine belt conveyor state on-line monitoring system based on DTS, Proceedings of SPIE - The International Society for Optical Engineering 8924, , Article number 89242I.
10. Kuttalakkani, M., Natarajan, R., Singh, A.K., Vijayakumar, J., Arunan, S., Sarojini, L., Sensor based effective monitoring of coal handling system (CHS), International Journal of Engineering and Technology 5/3, pp 2432-2435.
11. Wylomanska, A., Zimroz, R., , 2015. The analysis of stochastic signal from LHD mining machine Springer Proceedings in Mathematics and Statistics 122 pp. 469-478.
12. Bongers, D.R., Gurgenci, H., 2008.Fault Detection and Identification for Longwall Machinery Using SCADA Data, Complex System Maintenance Handbook, Springer Series in Reliability Engineering, pp 611-641.
13. Obuchowski, J. , Wylomańska, A. , Zimroz, R., 2014. Recent developments in vibration based diagnostics of gear and bearings used in belt conveyors, Applied Mechanics and Materials 683 , pp 171-176.
14. Zimroz, R., Wodecki, J., Krol, R., Andrzejewski, M., Sliwinski, P., Stefaniak, P.K., 2014. Self-propelled mining machine monitoring system - data validation, processing and analysis. Mine planning and equipment selection: proceedings of the 22nd MPES Conference, C. Drebenstedt, R. Singhal (eds.), Dresden, 1285-1294.
15. Jablonski, A., Barszcz, T., 2013 . Validation of vibration measurements for heavy duty machinery diagnostics. Mechanical Systems and Signal Processing, 38 (1), pp. 248-263.
16. Wylomanska, A. , Zimroz, R., 2014. Signal segmentation for operational regimes detection of heavy duty mining mobile machines - A statistical approach, Diagnostyka 15/2 pp 33-42.
17. Gajda, J., Sikora, G., Wyłomańska, A., 2013. Regime variance testing - A quantile approach. Acta Physica Polonica B, 44 (5), pp. 1015-1035. http://th-www.if.uj.edu.pl/acta/vol44/pdf/v44p1015.pdf, doi: 10.5506/APhysPolB.44.1015.
18. Cempel, C., Tabaszewski, M., 2007. Multidimensional condition monitoring of machines in non-stationary operation.Mechanical Systems and Signal Processing, 21 (3), pp. 1233-1241.
19. Zimroz, R., Bartkowiak, A., 2013.Two simple multivariate procedures for monitoring planetary gearboxes in non-stationary operating conditions. Mechanical Systems and Signal Processing, 38 (1), pp. 237-247.
20. Bartkowiak, A.,Zimroz, R., 2014. Dimensionality reduction via variables selection - Linear and nonlinear approaches with application to vibration-based condition monitoring of planetary gearbox Applied Acoustics 77, pp 169-177.
21. Jablonski, A., Barszcz, T., Bielecka, M., Breuhaus, P., 2013. Modeling of probability distribution functions for automatic threshold calculation in condition monitoring systems, Measurement: Journal of the International Measurement Confederation 46/1, pp 727-738.
22. Stefaniak P., Wyłomańska A., Obuchowski J., Zimroz R., 2015. Procedures for decision thresholds finding in maintenance management of belt conveyor system - statistical modeling of diagnostic data, in: Lecture Notes in Production Engineering, Christian Niemann-Delius ed., pp. 391-402, Springer.
23. Bartkowiak, A., Zimroz, R., 2011. Outliers analysis and one class classification approach for planetary gearbox diagnosis, Journal of Physics: Conference Series, 305 (1), art. no. 012031. doi: 10.1088/1742-6596/305/1/012031
24. Zimroz, R., Bartelmus, B., Barszcz, T., Urbanek, J., 2014.., Diagnostics of bearings in presence of strong operating conditions non-stationarity - A procedure of load-dependent features processing with application to wind turbine bearings, Mechanical Systems and Signal Processing 46/1, pp 16-27.